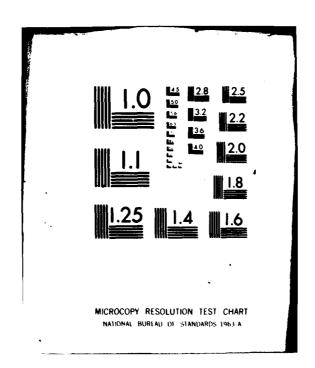
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OBJECTIVE PREDICTION OF SLANT VISUAL RANGE DURING ADVECTIVE FOG--ETC(U)
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OBJECTIVE PRODUCTION OF SEAST VISUAL RAVES

BURING ADVECTIVE FOR STILLATIONS



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and

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At the Air Force Geophysics Laboratory(AFGL) Weather Test Facility(WTF) at Otis Air Force Base, MA, an instrumented tower network has been utilized to explore techniques for the measurement of slant visual range (SVR) and the short range prediction of below-limit SVR conditions. SVR is defined as the slant distance to the farthest high intensity runway edge light or approach light which a pilot can see at decision height (DH) on the approach path. This paper will present the results of the AFGL development an I i valuation of a remote tower SVR system under Categories I and II operations. Three prediction techniques (Markov, REEP and Equivalent Markov) to yield probability estimates of below-limit SVR conditions are evaluated and comparisons made to determine their respective accuracy and reliability. Forecast times examined are 2,5,10,30 and 60 minutes.

TEST FACILITY AND DATA SETS

Development and testing of a SVR syst m are a part of the continuous evaluation of various meteorological measurement instruments at the AFGL WTF. Measurements of atmospheric extinction coefficient are made by an array of EG&G forward scatter meters (FSM) mounted on three towers (A,Q, and X) in the WTF, figure 1.

The WTF is located in the Cape Cod area where low visibility episodes are predominantly caused by heavy advection fog accompanied by light rain or drizzle. The continuous data stream from August 1977 to April 1979 revealed a systematic difference between the SVR and runway visual range (RVR) measurements. Figure 2 depicts a pre-irontal band of showers followed by a period of heavy advection fog. Note that during periods of moderate rain, the vertical gradient of extinction coefficient (10-|km-|) is

nearly zero. During the advection period, however, there is a significant increase of extinction with height.

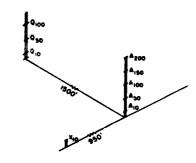


Figure 1. Configuration of Instrument lowers

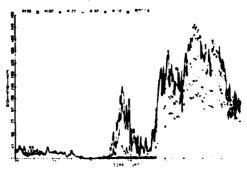


Figure 2. Tower A Extinction Coefficients 14-15 October 1978

SVR specification equations developed from a single set of these two types of low visibility episodes could reduce the probability of detecting a below-limit condition of SVR. In order to remove this systematic bias, the selection of low visibility episodes was restricted to the advection fog type. Episodes were selected by applying the criterion that the SVR in the landing zone

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(tower A) was lkm⁻¹ or more for a period of an hour or greater. Specification and prediction equations were defined from a dependent data set which consisted of twenty reduced visibility episodes and contained in excess of 6300 minutes of data. The independent data set, used to test and compare the various techniques, was drawn from twenty-five other episodes totalling over 9900 minutes of reduced visibility.

. SVR SPECIFICATION

3.1 Category II

Hering and Geisler (1978) demonstrated the accuracy of FSM measurements as specifiers of SVR under Category II conditions. Those results also indicated that during advection fog conditions observed at Cape Cod, a 50 ft remote tower system yields SVR estimates nearly as accurate as a 100 ft remote tower system in which point visibility measurements are made at the same height as the Category II DH.

The earlier study compared a method which used remote tower measurements of visibility to specify approach zone SVR (ASVR100) to a method which relies on the touchdown RVR measurement. Table 1 summarizes the relevant statistics for the tower option which relies on measurements at 50 ft (ASVR100) and the control technique.

STATISTIC	ASVRIOD	RVR
CORRELATION COEFFICIENT PER CENT RMSE BIAS	.979 25.4 1.4	. 966 40.0 -37.9
THRESHOLD: 5 km ⁻¹ 15 POD FAR	90 95 3	71 71 9
THRESHOLD: 12. km ⁻² TS PGD FAR	87 92	47 47

Table 1: STATISTICS CATEGORY II SPECIFICATION

The threshold 5 km⁻¹ corresponds to about 1/2 mile (800 m) daytime visibility and 1 mile (1600 m) at night. The threshold 12 km⁻¹ corresponds to 1/4 mile (400 m) daytime and 1/2 mile at night. Clearly, ASVR100 yields superior specifications of ASVR100 than does RVR. Figure 3, which is a time series plot of an advection fog episode, demonstrates that the major deficiency of the RVP method lies in the persistent optimism it conveys to the pijot at DH of seeing his reference point.

3.2 Category 1

Specification equations for 200 ft SVR (ASVR200) were developed using FSM measurements at discrete points in the vertical are converted to a weighted vertical average which is used to represent SVR in the approach zone through

ASVR200=(A200+2A150+2A100+2A50+A10)/8

Application of a multiple linear regression technique to a dependent data set yielded specification equations for ASTR200 as follows:

Table 2 summarizes the relevant statistics for these specification equations and the control technique (RVR)

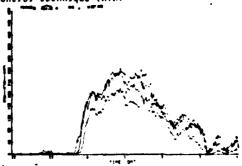


Figure 3. One Minute Average Value of ASVRICE.

ASVRIOO and RVR for Advection Fcz
14-15 October 1978

STATISTIC	ESTI	E572	8/8
CORRELATION COEFFICIENT PER CENT RMSE BIAS	. 971 91.8 -5.6	931 44. 1 -11. 2	900 54. 9 92. 9
THRESHOLD: 5 km ⁻¹ TS POD FAR	90 91 2	4	55 55
THRESHOLD 12 km ⁻¹ TS POD FAR	87 91 5	70 71 1	37 0

Table 2. STATISTICS CATEGORY I SPECIFICATE 5

Unlike the results under Lategory II conditions, the statistics of Category I conditions show that the 100 ft method (ESTI) out performs the 50 ft method (ESTI) out performs the 50 ft method (ESTI) out performs the soft method (ESTI) by nearly 15 percentage points in the RMSE. Similar differences exist in the other statistics. Again we find the remote tower equations are superior to the touchdown RVR measurement. To demonstrate these results we select ASVR200, RVR and ASVR200 (redesignated ESTI) and display them in a time series of an advection fog episody in figure 4. Note the stubborn bias of the RVR measurement withe ASVR200 closely tracts ASVR200.

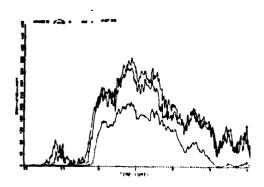


Figure 4. One Minute Average Value, of ASVR200, RVR and ASVR200 for Advection Fog 14-15 October 1978

. PREDICTION TECHNIQUES

4.1 Markov Model

Gringorten (1972) adapted for meteorological use a special class of the Markov chain called the Ornstein-Uhlenbeck process. The conditional probability estimates are derived from the uncategorized initial condition as given by the latest observation of the predictand and are based upon an exponential decay of the autocorrelation coefficient with time. An assumption is made which equates the cumulative frequency distribution (CFD) of prevailing visibility to the CFD of SVR. This is a necessary assumption because there does not exist a SVR data base to accurately determine its CFD. A twenty-three year data base for Otis AFB was used to determine the unconditional CFD of prevailing visibility as a function of time of day and season.

SVR_O (SVR at time t_O) for Categories I and II conditions were obtained from regression equations which yield specifications of ASVR200 and ASVR100. These specification values were used as inputs into the model.

4.2 Regression Estimation of Event Probabilities (REEP)

REEP (Miller, 1964) calculates probabilities of being within categories which can be easily converted into exceedance probabilities. Instead of transforming the initial SVR into a most probable SVR from which an exceedance probability can be found (Markov model), REEP uses the initial SVR directly.

Five predictand category limits were selected to coincide with the thresholds prescribed beforehand. Category limits were assigned to each predictor based on the relative frequency distribution of the SVR values in the dependent data set.

REEP is formulated to insure internal consistency among predictand

categories such that the sum of the probabilities totals unity. This is inserted by using the same predictor categories for each predictand equation. REEP prediction equations were generated from a randomly selected sub-sample of 3000 observations from the dependent sample.

4.3 Equivalent Markov based on PEET

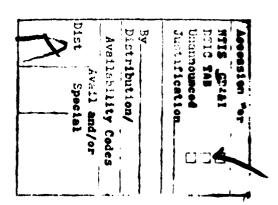
The classical Markov transition Matrix M can be used in preparing forecasts for any number of time steps (n) in the for roby using powers of M. A prediction method that yields probabilistic forecasts compared to the classical Markov process but without the necessity of utilizing M explicity (M. Mor. 1968) uses the coefficients from a serent REEP equations to determine the one-top transition matrix P.

Experience with the model resulted in the use of two separate transition matrices to cover the full range of predictions. For Category II operations, a five minute enestep transition matrix computes conditional probabilities for forecasts of five minutes or greater. For Category I operations, a two minute one-step transition matrix is used to compute two and five minute forecasts and a ten minute one-step transision matrix is used to compute forecasts of ten minutes or greater.

5. RESULTS: PREDICTION TECHNIQUES

The probability forecasts are evaluated through the use of the P-score as defined by Epstein (1969) and Murphy (1969) and by reliability graphs. The P-score represents the mean squared difference between the forecast and observed probability distributions. The three prediction techniques were applied to each of the twenty-five independent data episodes. The results of each episode were combined to reflect the overall accuracy and reliability.

Verification results of the Fscore for Category I operations given in
Table 3 reflect that the Equivalent Markov
technique yields a slight improvement over
the Markov and REEP techniques (2 percent
and 9 percent respectively). Figures 5 to 7
depict the reliability of the three techniques
for 10 minute predictions. Clearly the
predicted probabilities of the Equivalent
Markov and REEP techniques are quite close
to the observed frequencies. However, the
predicted probabilities of the Markov
technique tend to underestimate the observed
frequencies.



	PREDICTION TECHNIQUE		
LAG	MARKOV	REP	EQUIV-MARKOV
2	. 046	.048	.065
5	.655	. 060	. 035
10	.075	.081	.074
10	.131	, 139	.129
•	. 172	, 196	. 169
	l		

Table 3. P-SCORES CATEGORY I

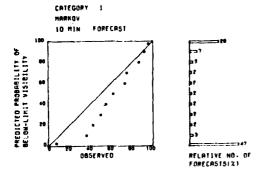


Figure 5. Reliability Graph Markov Category 1

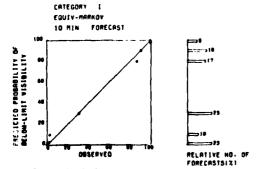


Figure 6. Reliability Graph Equivalent Markov Category 1

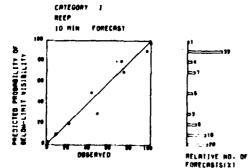


Figure 7. Reliability Graph REEP Category I

Table 4 summarizes the restriction Category II operations. The Lip (value time) technique yields systematically better is a cover the Markov and RELP techniques.

PREDICTION TECHNIQUE			
LAG	MARKOV	REEP	EQUIV WAREOV
,	. 014	.018	017
,	. 021	,019	Ula
10	. 02%	.075	. 674
×	.652	.00	.044
	.667	. 1766	,65a
			ŀ

Table 4. P-SCORES CATEGORY 11

A dropotf in skill of the Equivalent Markov technique, as the forecast interval is increased from 10 to 60 minutes, is due in part to decreasing resolution in the low probability forecasts. The percentage of forecasts in the 0-5 percent range lowers from 85 to 72 to 58 present.

6. CONCLUSIONS

Analysis of the data collected at the AFGL WTF demonstrates the accuracy and reliability of a remote tower system. For both Categories I and II operations such a system would provide a probability of detection of below-limit conditions of 41 percent or better, a large improvement over using the surface RVR instrument. The Equivalent Markov prediction technique was shown to provide accurate and reliable forecasts of below-limit SVR conditions and yield slightly better results on independent data than did the Markov and REEP techniques.

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of detection of below-limit SVR conditions of 91%. The Equivalent Markov technique is shown to provide accurate and reliable forecasts and yield slightly better results than Markov and REEP.

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